High-Dimensional Anomaly Detection with Radiative Return in e^+e^- Collisions

Julia Gonski, Jerry Lai, Benjamin Nachman, Inês Ochoa

1 September 2021

Energy Frontier Kickoff Workshop

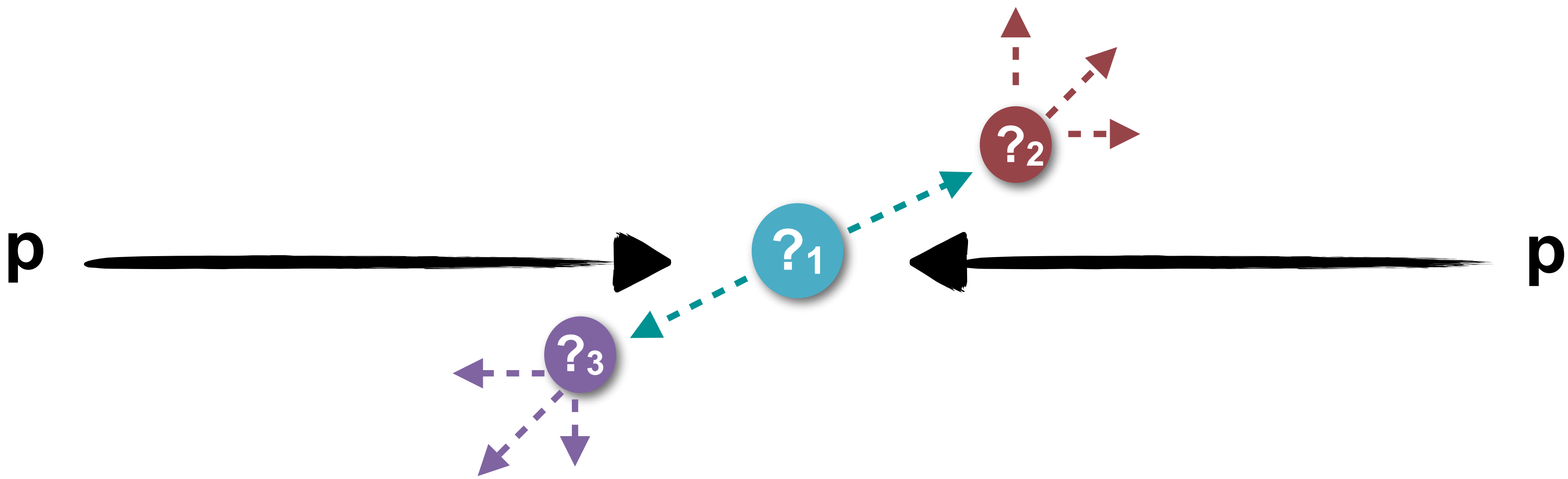
arXiv:2108.13451

Outline

- Motivation
  - Anomaly detection in HEP
  - e^+e^- & radiative return
- Strategy
  - Dataset details/samples
  - Training setup & the CWoLa method
- Results
  - Data vs. simulation (semi-supervised)
  - Background-only training (weakly supervised)
- Experimental outlook & conclusions

Anomaly Detection in HEP

- **Anomaly detection (AD)** = identify features of the data that are inconsistent with a background-only model
- At the **Large Hadron Collider**: no recent new physics + many exclusion results → develop strong model independent search program
  - Weakly supervised learning in dijet final states (ATLAS)
  - LHC Olympics 2020: cross-experiment/theory “competition” of AD methods
  - Dark Machines anomaly score challenge

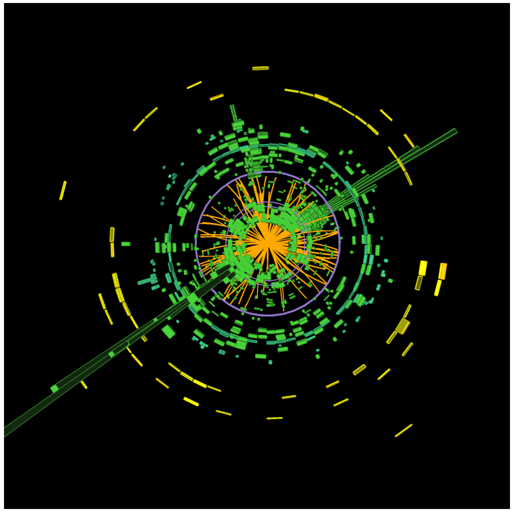


AD Beyond the LHC

- **Snowmass 2022**: several e^+e^- colliders (ILC, FCCee, CEPC) are strong candidates for the next international accelerator

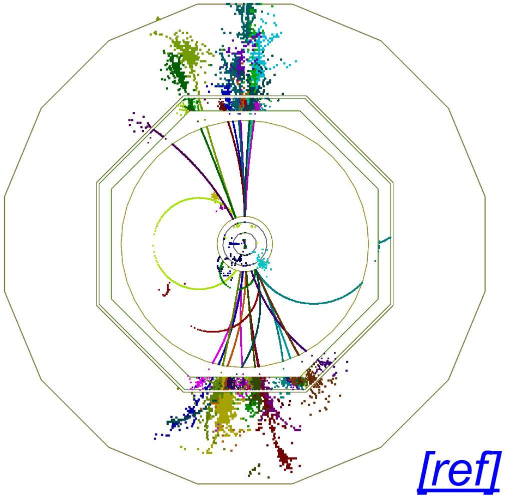
- **How to exploit anomaly detection in an entirely different type of particle collision?**
  - Many crucial differences in hadron vs. e^+e^- events: initial state knowledge, background processes, pileup, detector info

pp $\rightarrow$ dijet, $\sqrt{s}$=13 TeV LHC



[ref]

$e^+e^- \rightarrow WW \rightarrow q\bar{q}q\bar{q}$, $\sqrt{s}$=1 TeV ILC



[ref]

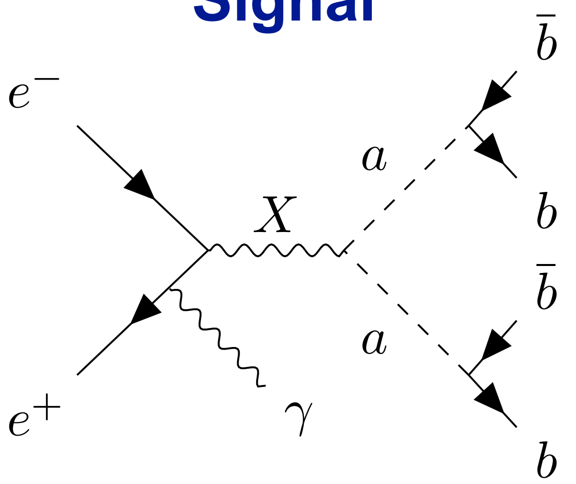
e^+e^- Dataset

- **Signal:** 700 GeV scalar $X \rightarrow$ 2 100 GeV scalars $\boldsymbol{aa} \rightarrow b\bar{b}b\bar{b}$
- **Background:** Drell-Yan hadronic decays

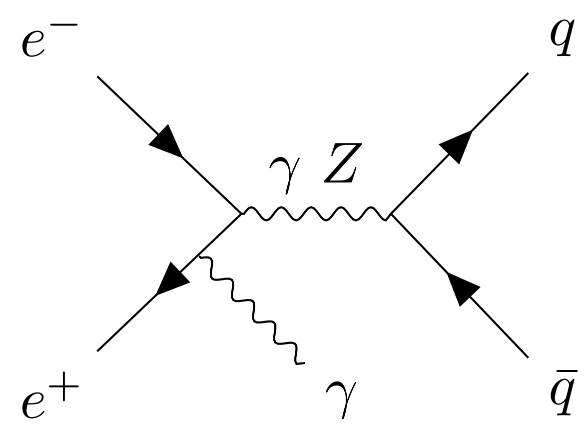
- Reconstruct dijet final state with R=1.0 jets built from particle flow objects

- Generate e^+e^- collisions at $\sqrt{s}$ = 1 TeV (Madgraph)
  - Pythia showering/hadronization + Delphes detector simulation (using general ILC card)
  - Emulate training scenario with "full dataset" of ~6.5 ab^{-1}

Signal



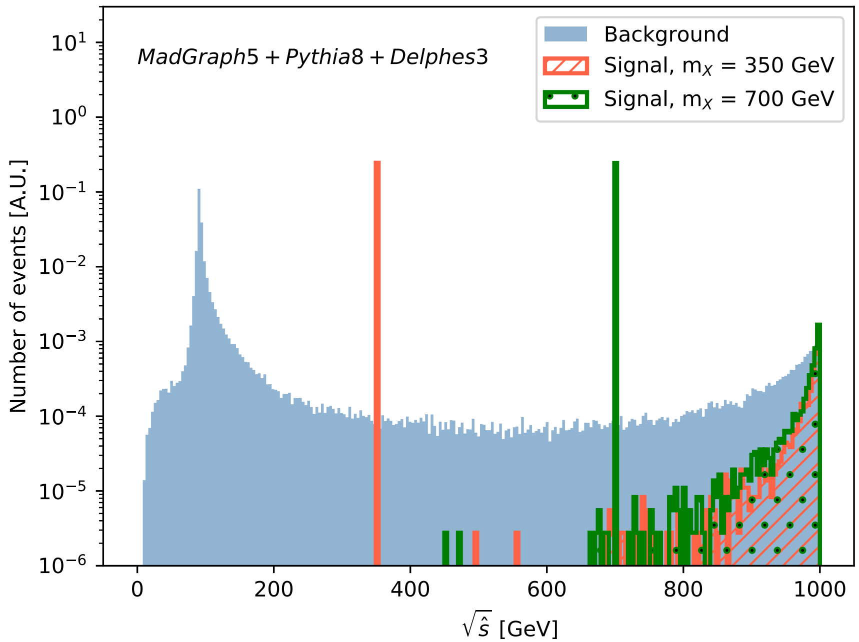
Background



Radiative Return in e+e-

- Require events to have at least 1 photon with E > 10 GeV from initial state radiation (ISR)
  - ISR photon can have any energy
  - Initial CoM energy in e+e- is exactly known
- Can use to "scan" new particle masses, à la dijet invariant mass bump hunts at the LHC

350 GeV *X*
~ 650 GeV ɣ



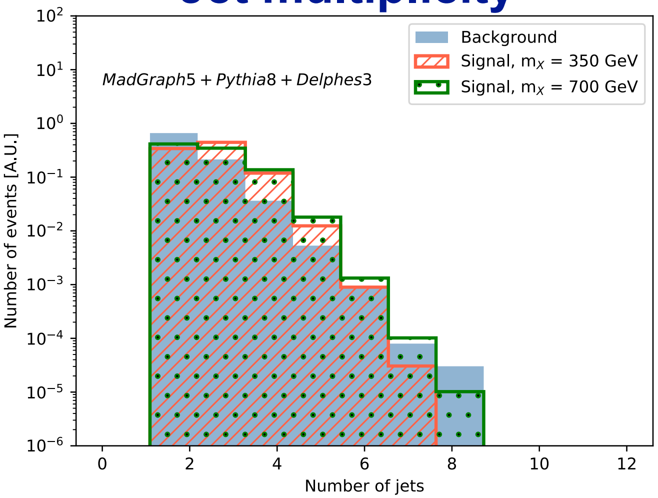
700 GeV *X*
~ 300 GeV ɣ

Training Setup

- Using **Particle Flow Networks** implemented in [EnergyFlow framework](): model an event as an unordered, variable-length set of jets
  - Up to 15 jets per event
  - 10 features per jet: 4 vector (pT, η, ϕ, m), b-tagging bit, 5 N-subjettiness variables τ

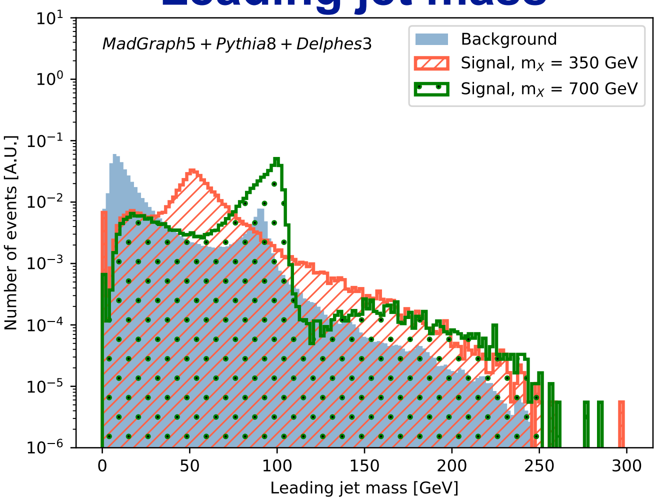
➡**150 input features per event**

Jet multiplicity



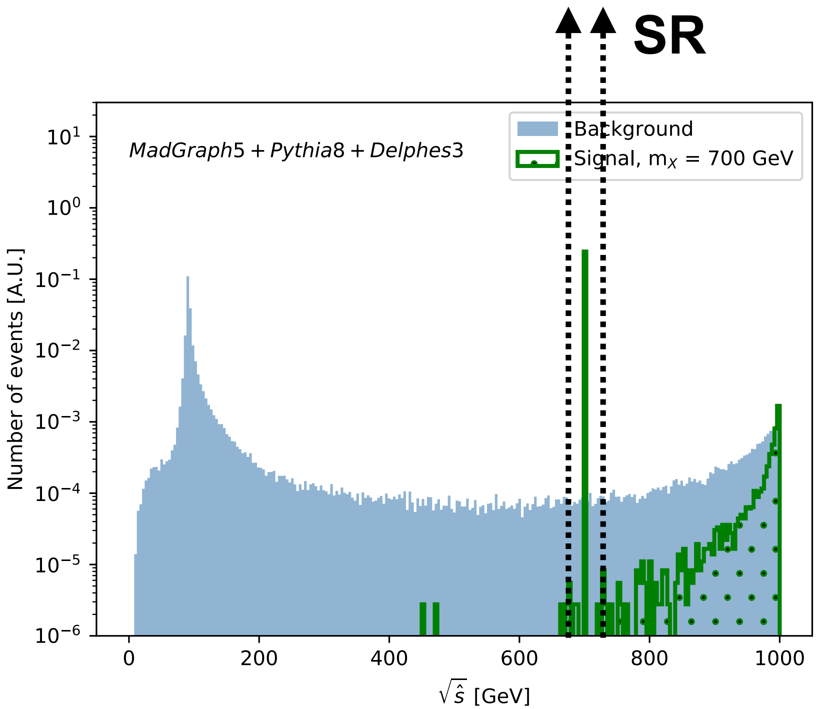
- **Normalization**: normalize jets to average p_T/η/ϕ in event — critical to not induce √s sculpting
- **Ensembling**: train 50 models per setup with random signal injections, quantile scale outputs, and average

Leading jet mass



Semi-supervised (Data vs. Simulation)

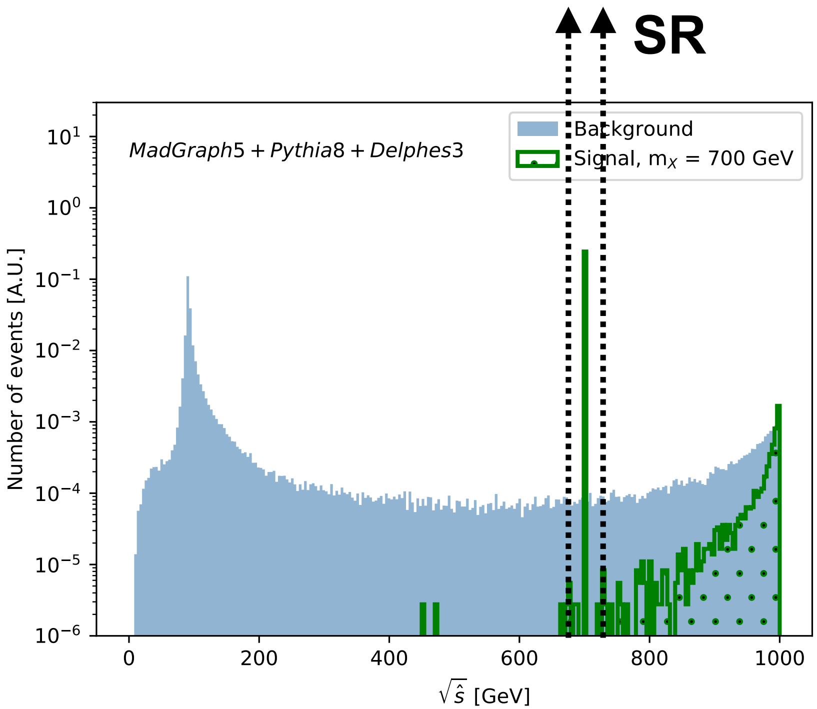
- Select signal and background in ±25 GeV windows in √s around the resonance mass: SR = [675, 725)
- Train with a variety of signal contaminations: σ=0.0, 0.5, 1.0, 2.0, 3.0, 5.0, and ∞ (eg. all S vs. all B)



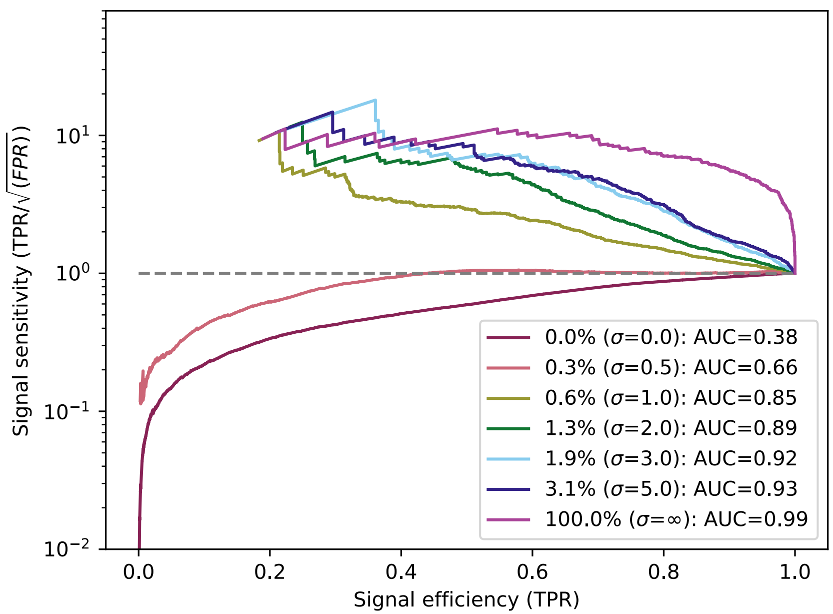
Semi-supervised (Data vs. Simulation)

- Select signal and background in ±25 GeV windows in √s around the resonance mass: SR = [675, 725)
- Train with a variety of signal contaminations: σ=0.0, 0.5, 1.0, 2.0, 3.0, 5.0, and ∞ (eg. all S vs. all B)

➡ Significance Improvement Characteristic (SIC): can enhance a 0.6% signal contamination from 1.0σ to ~10.0σ

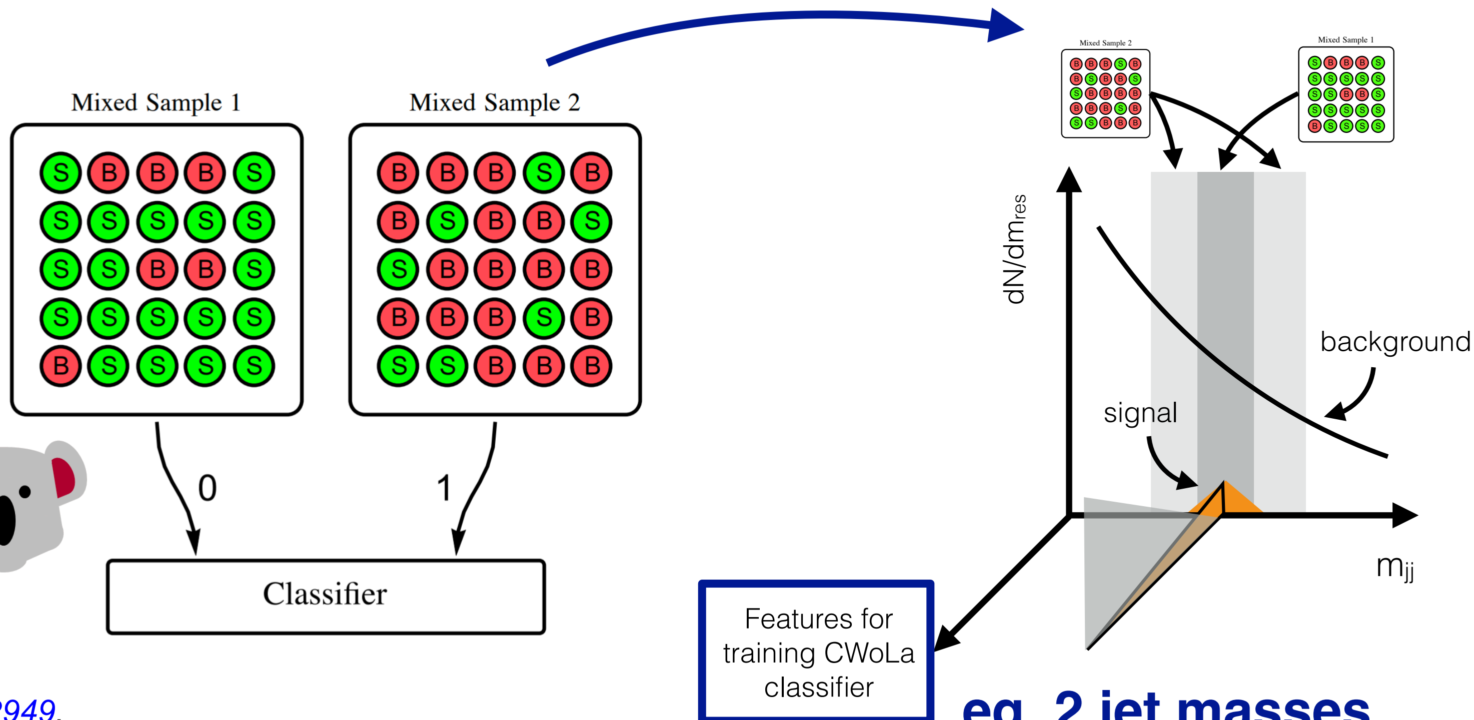


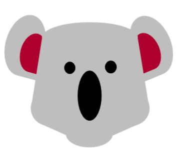
SIC: X=700 GeV vs. bkg



Data-Driven/Weakly Supervised (CWoLa)

- NN trained in signal region vs. sideband is sensitive to signal vs. background characteristics
  - SR and SB defined in windows of m_{jj}, each region has different fraction of signal





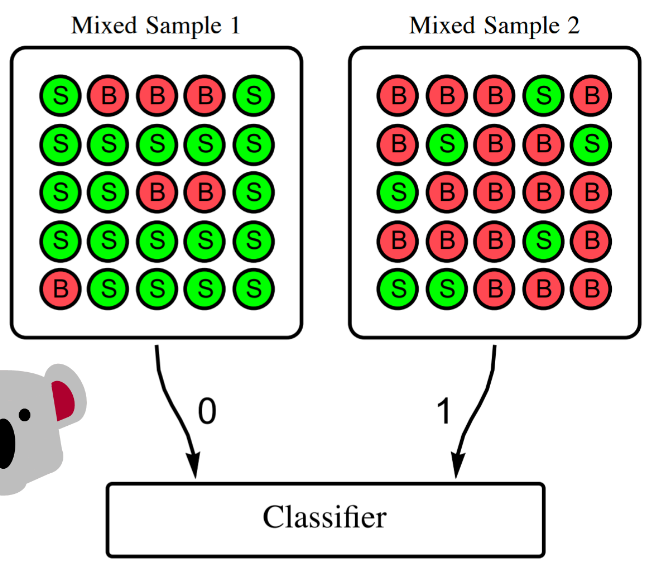
eg, 2 jet masses

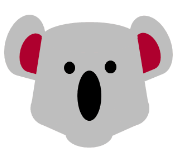
1708.02949, 1805.02664

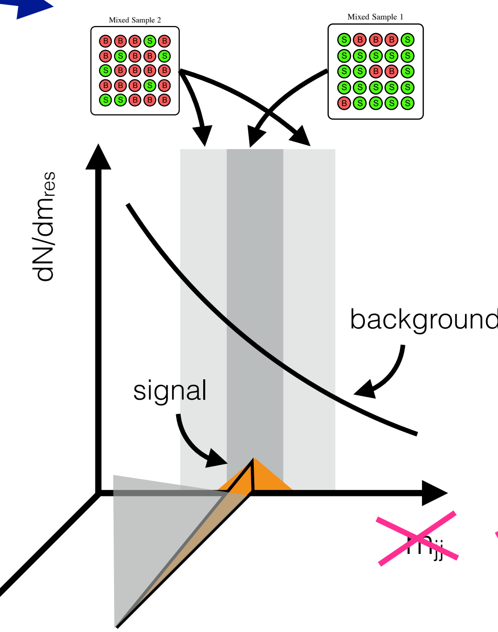
Data-Driven/Weakly Supervised (CWoLa)

- NN trained in signal region vs. sideband is sensitive to signal vs. background characteristics
  - SR and SB defined in windows of m_{jj}, each region has different fraction of signal

In our case…







~~m_{jj}~~ $\sqrt{s}$

Features for training CWoLa classifier

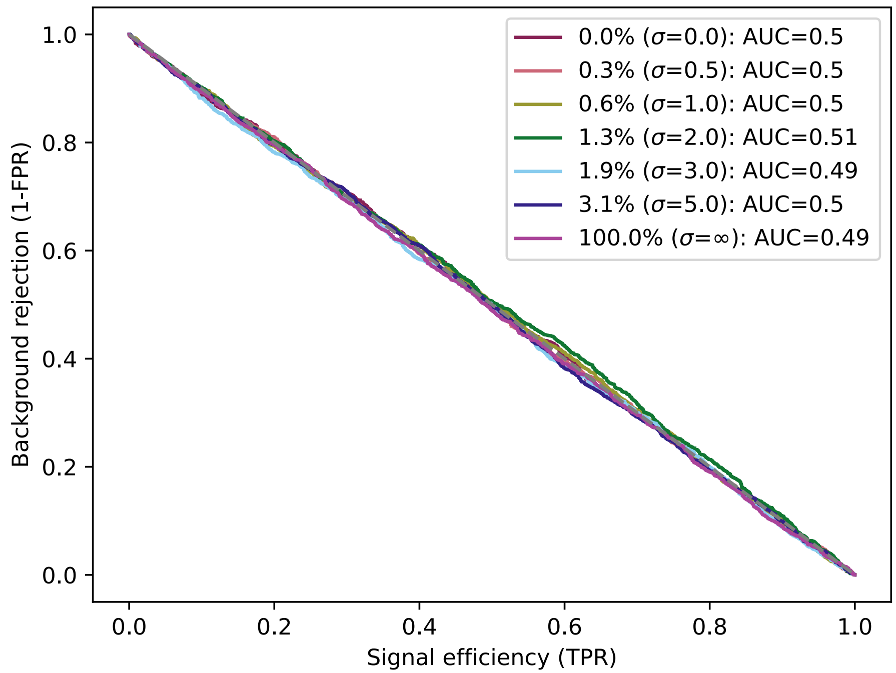
150 per event!

[1708.02949](https://arxiv.org/abs/1708.02949), [1805.02664](https://arxiv.org/abs/1805.02664)

Monitoring √s Correlation

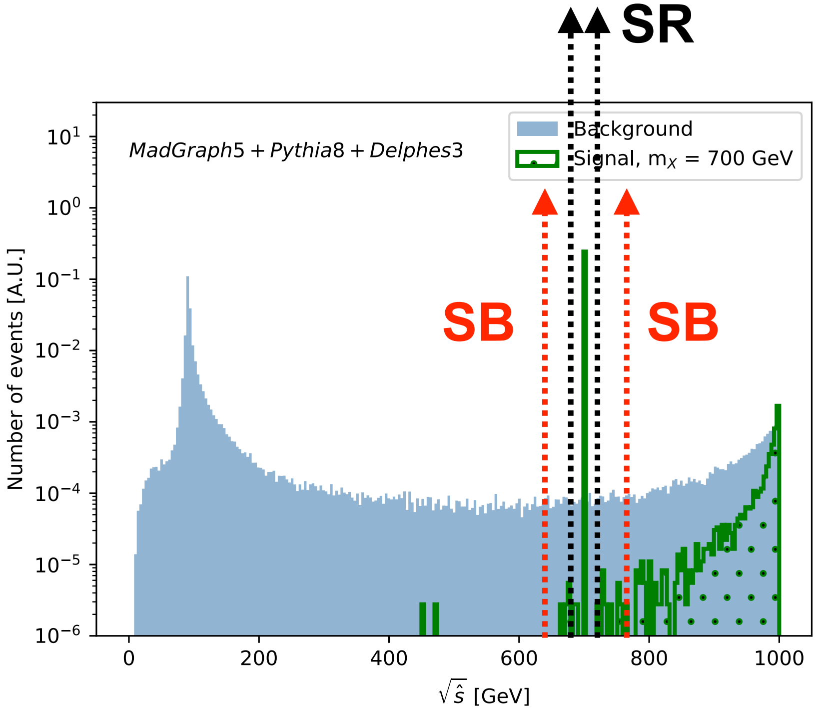
- Shift to CWoLa training means signal and background are in different √s bins
  → Need to validate extrapolation across √s & ensure little/no correlations
- CWoLa-trained classifier tested on background in SB vs. background in SR has learned nothing to discriminate on √s alone

ROC: Bkg in SB vs. Bkg in SR



Weakly Supervised Results

- SR = [675, 725); sideband in ±50 GeV windows around SR= [625,675) U [725,775)

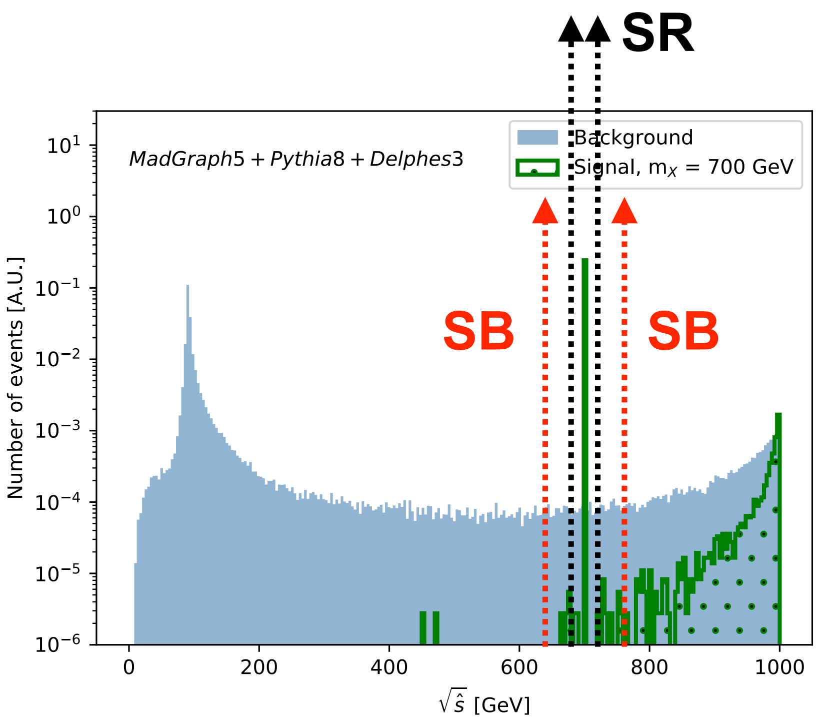


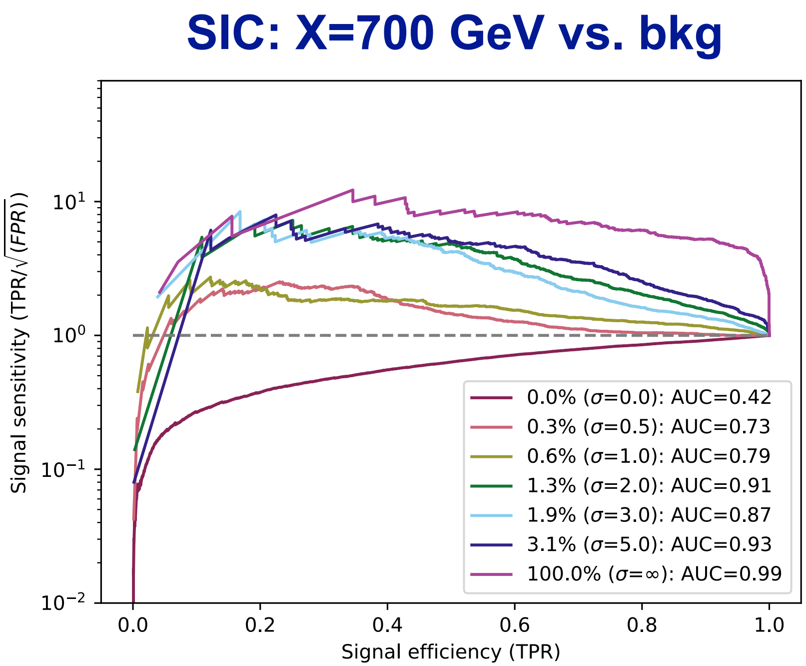
Weakly Supervised Results

- SR = [675, 725); sideband in ±50 GeV windows around SR= [625,675) U [725,775)

➡ **Little degradation in performance from removing signal hypothesis: 1.0σ excess enhanced to ~3.0σ**

  - Other contaminations have even smaller discrepancies

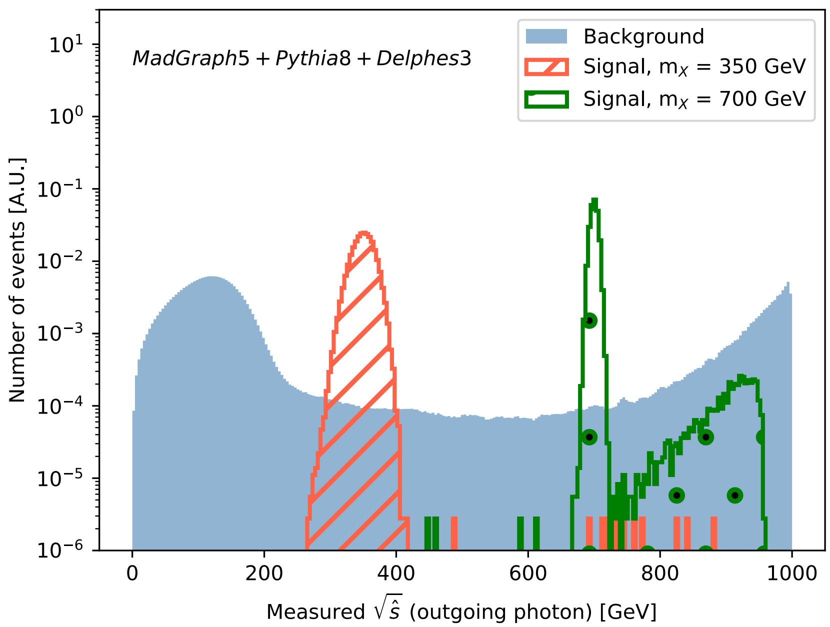




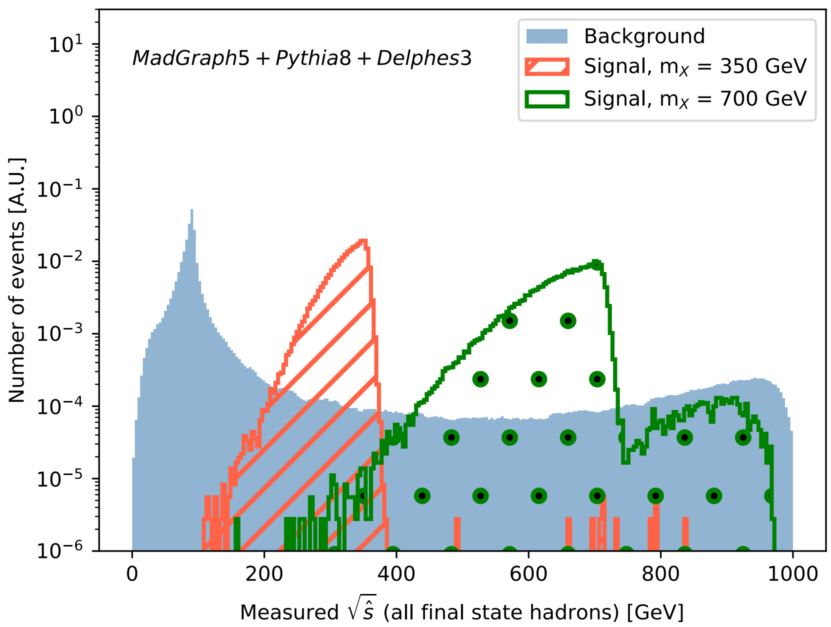
Experimental Outlook

- Detector features such as mass resolution and forward acceptance have strong impact on radiative return AD analyses
- Investigating different √s reconstruction measures to understand dependency and inform e+e- detector design

Measured √s, photon captured



Measured √s, photon lost



Conclusions

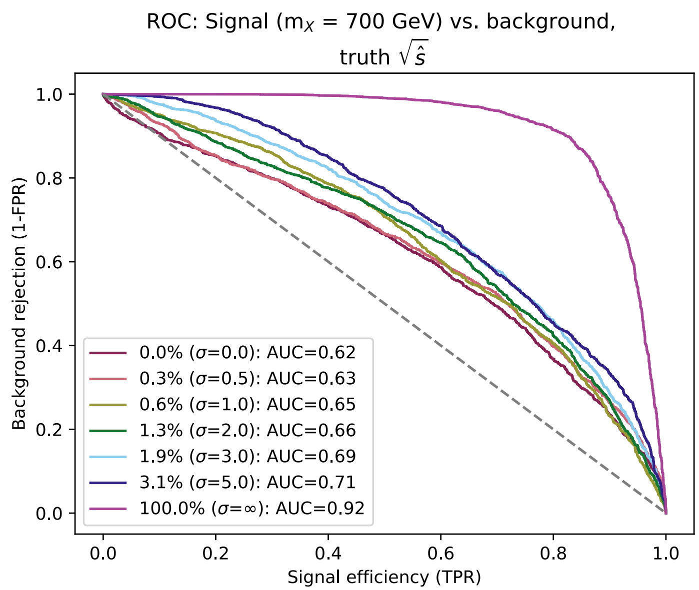
- Successful application of anomaly detection to a novel e^+e^- collision dataset
- Strong performance from **high dimensional Particle Flow Network** training inputs in labeled data vs. simulation classification
- Shift to data-driven training via CWoLa method shows little degradation, and **enhanced sensitivity to a generic new physics signal with no signal prior**
- **On the arXiv as of this morning! arXiv:2108.13451**
  - Comparison of performance in various measures of $\sqrt{s}$
  - Sensitivity to lower mass X resonance (350 GeV)
  - Comparison to sensitivity from e^+e^- event-level variables

Backup

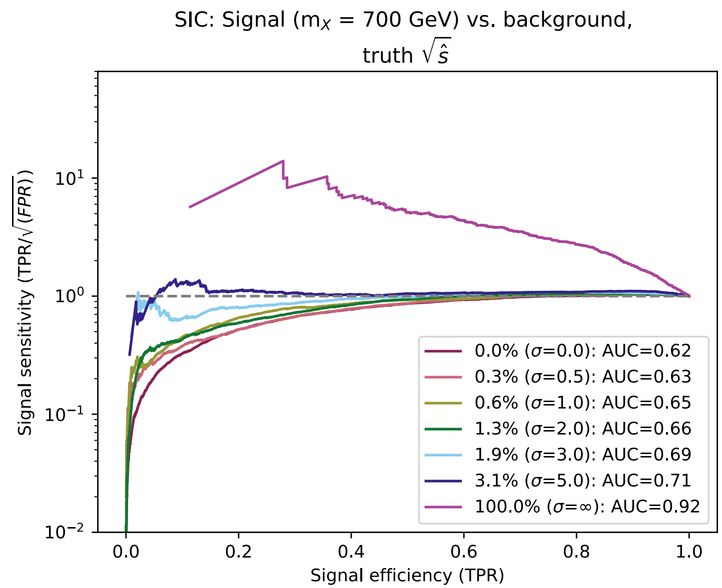
Event Level Variable Results

- Training features: 15 per event
  - Masses: leading & subleading large-R jet, total jet mass
  - Transverse momenta: leading & subleading large-R jet, leading photon, j1 pT / ɣ1 pT, reconstructed X, X pT / ɣ1 pT
  - Multiplicities: # particle, # jets
  - Aplanarity, sphericity, transverse sphericity
  - ln(y23), calculated with all jets in the event

ROC

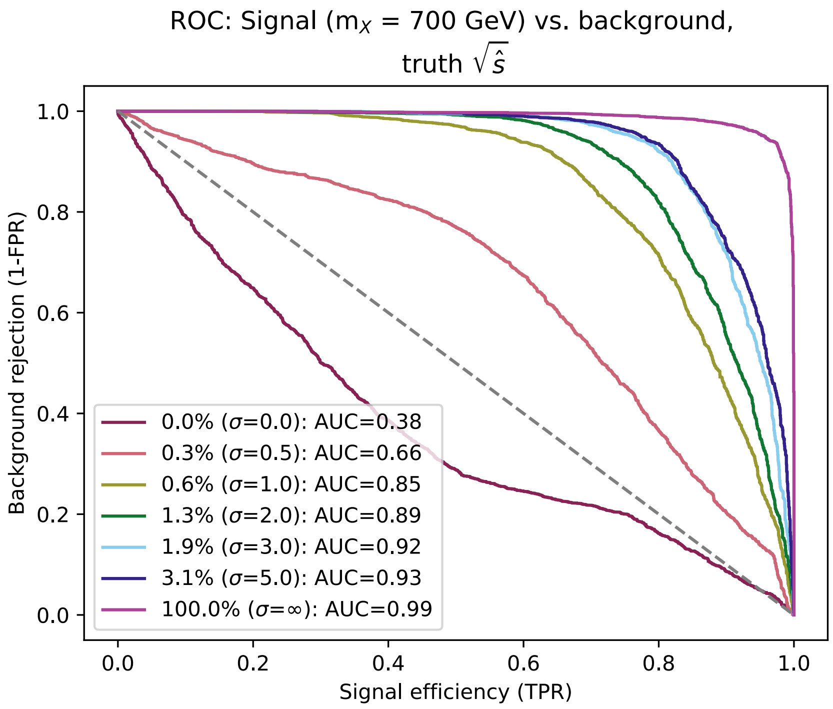


SIC

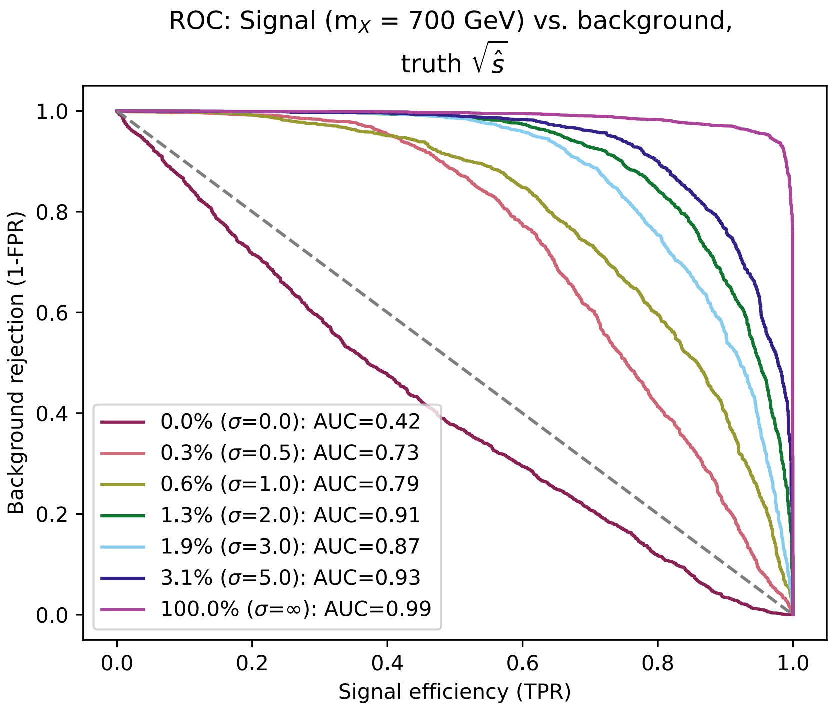


Training Result ROC Curves

S vs. B Training



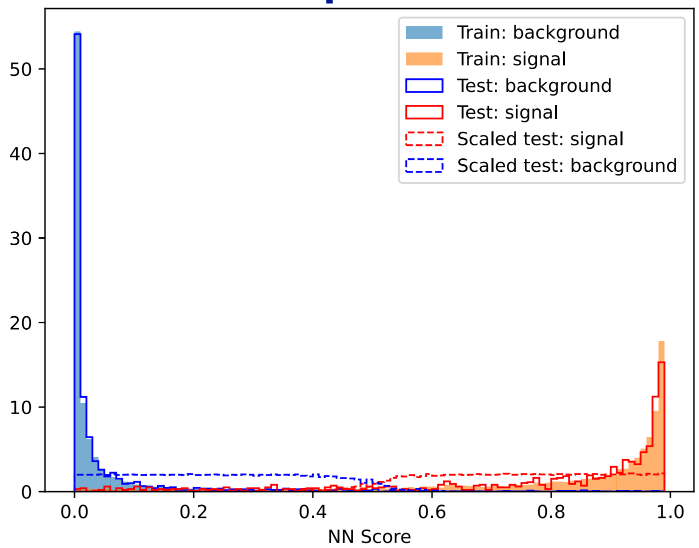
CWoLa Training



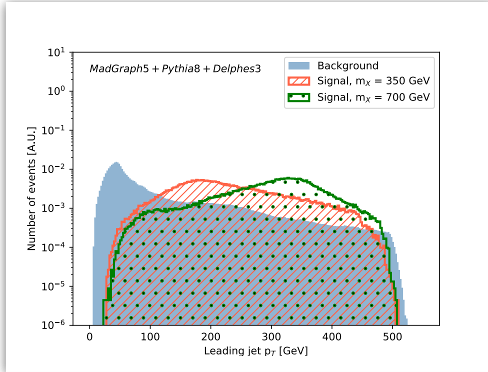
Neural Net Setup

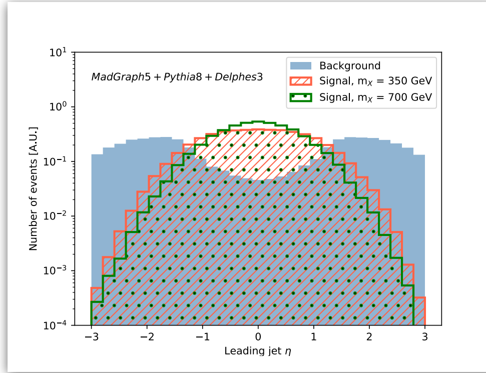
- Train over 50k events:
  - 25k background only
  - 25k with signal contamination of fixed percent
  - Test set = 10% of training (50% signal, 50% background)
- 30 epochs, batch size 100
- Adam optimizer with initial learning rate 0.0001
- Architecture: dense sizes (100, 100), Phi/F sizes (20, 20, 20)

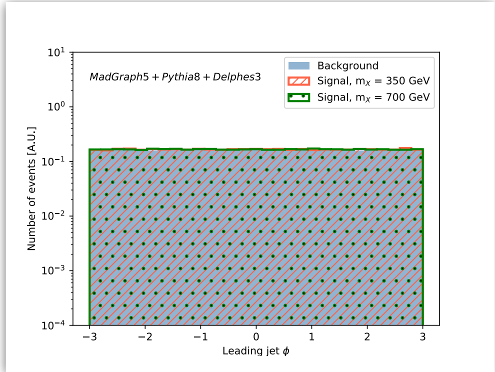
NN Output Score

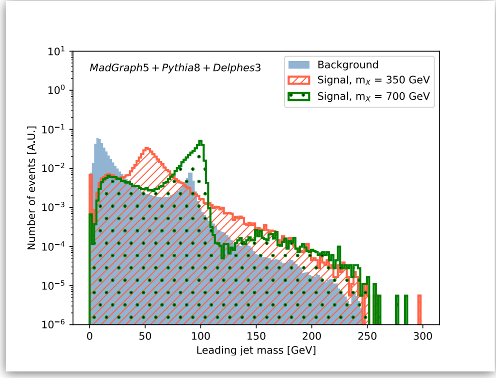


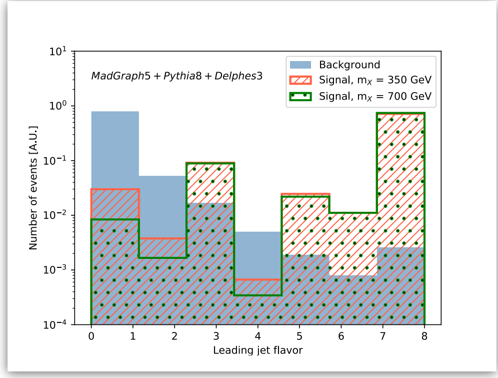
Leading Jet Training Inputs

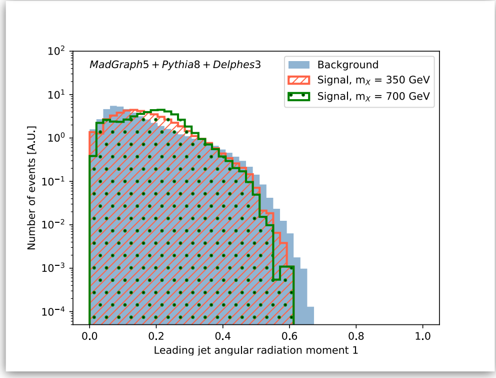


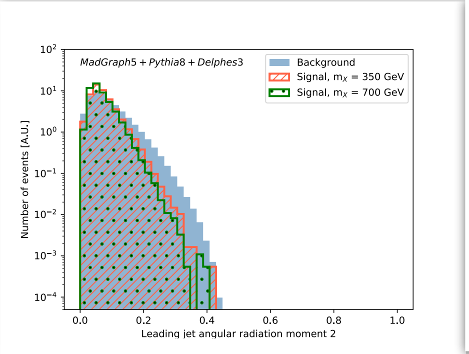


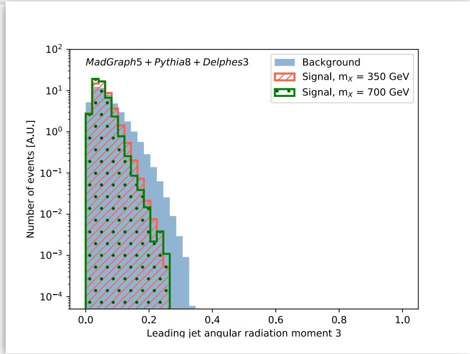


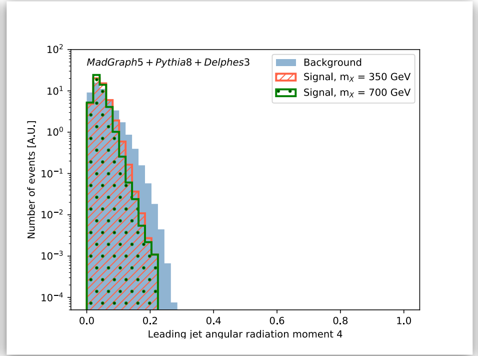


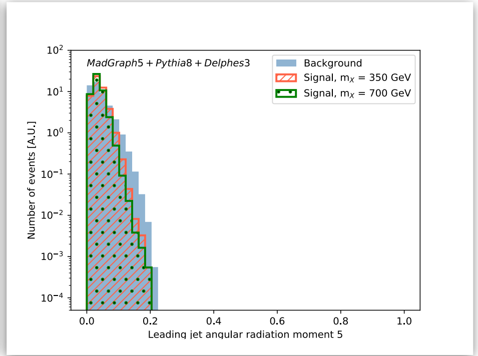




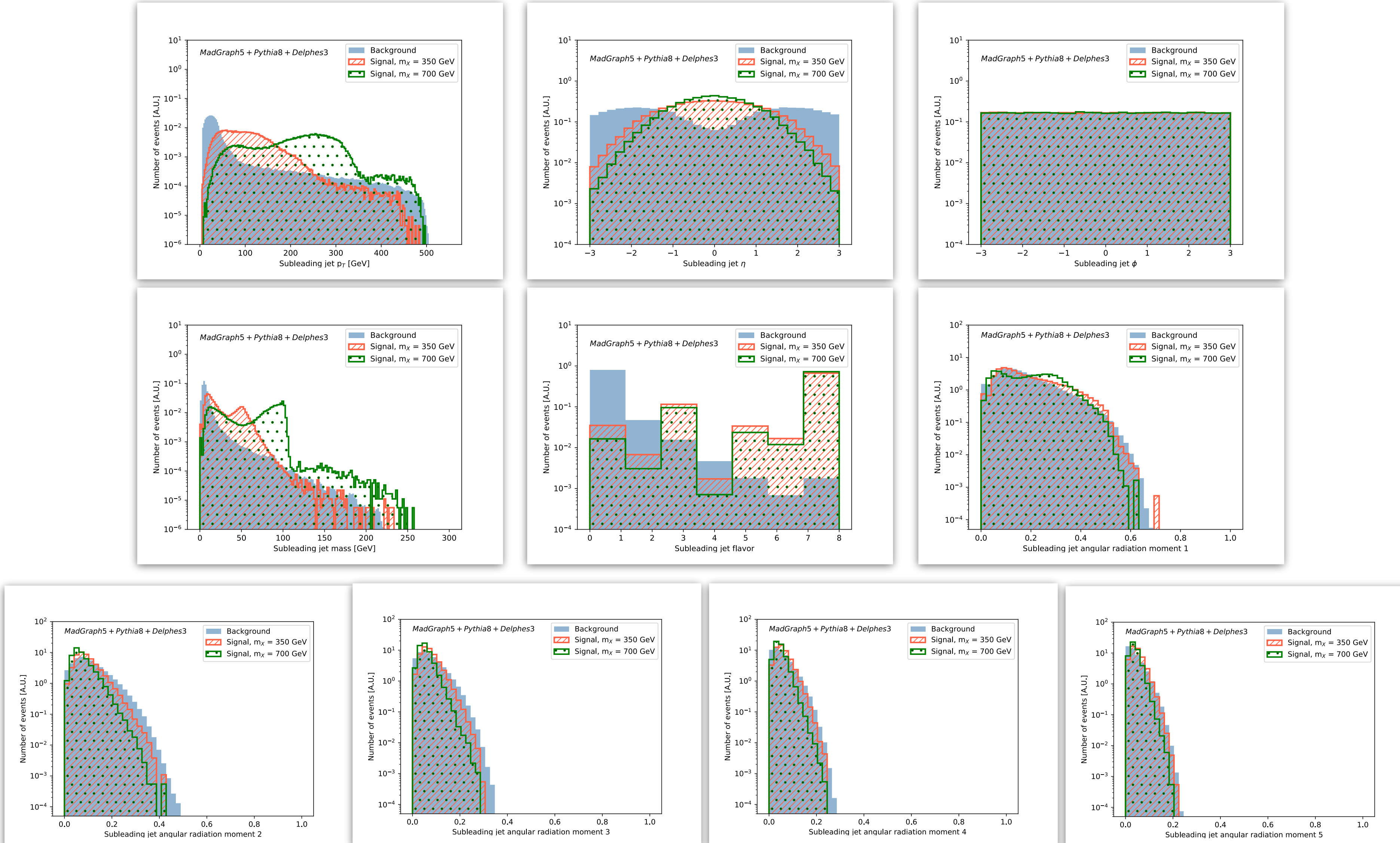








Subleading Jet Training Inputs



A Word on Jets

- **Jets** = sprays of hadronic particles reconstructed with clustering algorithms into a cone
- Higher mass exclusions for new particles + high energy collisions = high momentum outputs
  - **Constituents:** individual hadrons in jet
  - **Boosting:** collimation of constituents due to high momentum parent
  - **Substructure**: synthesizing correlations between jet constituents to determine particle content in large radius jet